Author(s): Hall, Andreas & Ahonen-Rainio, Paula & Virrantaus, Kirsi

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Knowledge and Reasoning in Spatial Analysis

Key words: reasoning, knowledge, spatial analysis, causal graph, sketches

Abstract

Reasoning is an essential part of any analysis process. Especially in visual analytics the quality of the results of the process depends heavily on the knowledge and reasoning skills of the analyst. In this study, we consider how to make the results transparent by visualizing the reasoning and the knowledge, so that persons from outside can trace and verify them. The focus of this study is in spatial analysis, and a case study was carried out on a process of mobility analysis. In the case study linked views of a map and a PCP were identified as reasoning artifacts. The knowledge used by the analyst is formed by these artifacts and the tangible pieces of information identified in them, along with the mental models of the analyst´s mind. The tangible pieces of information were marked with sketches and the mental models were presented in causal graphs because it was found that causality was central to the reasoning process in the case study.

1 Introduction

Experts in all fields reason, but they seldom tell us anything about how they do it. Usually the entire focus is laid on the outcome of the reasoning, not on the reasoning that actually led there. In many cases this might be satisfactory, as a successful outcome is often evidence enough that the reasoning behind it is of the required standard, but sometimes the reasoning itself needs to be studied. For example, when the outcome needs to be trusted before it can be put into use there must exist a trust in the reasoning that led to it. The question is: how can this reasoning be trusted if it is not accessible?

In this paper the problem is studied in relation to spatial analysis performed by applying a visual analytics approach. The term spatial analysis covers a set of methods whose results change when the location of the objects being analyzed change (Longley et al. 2011, p. 353), in other words, whose results are spatially dependent and spatially varying. In this paper visual analytics is considered as an umbrella concept for all analysis tasks that are carried out with the help of interactive visual interfaces using visual, mathematical (often statistical), and computational analysis methods. Thus, this paper focuses on expert reasoning in connection with the use of interactive visual, mathematical, and computational analysis methods in a spatial context.

The problem of inaccessible reasoning is present in visual analytics where the quality of the analysis results is often heavily dependent on the reasoning skills and the personal knowledge of the analyst, i.e. the expert. Thus, trust in the results is dependent on trust in the analyst. If the analyst, for example, is from another organization, there might be a lack of trust, but if the analyst´s reasoning could be evaluated trust might still develop. For this to happen, the analysis results need to be made transparent, i.e., it must be possible to access the reasoning that led to them. This problem has started to gain attention in research only recently (Nikander 2012).

Thomas and Cook (2005) called for measures that support the analytical reasoning process. Amongst other things they recommend that we should develop knowledge representations to capture, store, and reuse the knowledge used in the entire analysis process. These kinds of knowledge representations could also be used in order to make the analysis results transparent. As knowledge has to be re-constructed by each individual in his or her own mind, in contrast to information which can exist in explicit form outside our minds, its transfer is not straightforward. Knowledge Visualization addresses this problem. It “examines the use of visual representations to improve the transfer and creation of knowledge between at least two persons” (Burkhard 2005, p. 23).

Some efforts have been made to answer the call for action by Thomas and Cook (2005), such as studies aiming at understanding a user’s reasoning process through the study of their interactions with visualizations (called analytical provenance). For example, Jankun-Kelly et al. (2007) present a model that offers an approach to tracking an analysis process that allows users to see where they have been, where they are, and possibly where they might go next in the analysis process. Shrinivasan and Wijk (2008) developed a framework that supports analytical reasoning by enabling mental models to be externalized and the analysis artifacts to be linked to the visualizations and allowing revisits to the visualization states. Gotz and Zhou (2009) implemented a system that enables its users to save a visualization state along with the steps in the analysis process that led to it. These studies were all performed inside a single analysis application but studies aiming at creating a general infrastructure for the capture of provenance have also been carried out, such as Silva et al. (2007). These and other recent exemplars of progress in the visual analytics research field are identified by Pike et al. (2009). There are relatively few studies that were performed in a spatial context but some can be found. Xiao et al. (2006) presented a system that supports reasoning about network traffic but without taking spatiality into consideration. The research of Tomaszewski and MacEachren (2006) explicitly considers the spatial context but with the goal of supporting group work. The work of Burkhard (2005) takes the knowledge management perspective, with a focus on the communication of knowledge.

Previous work concerned with the reasoning process of an analyst has mainly focused on supporting the analytical reasoning process. The solutions produced generally take the needs of the analyst(s) into consideration but not the needs of people external to the analysis process. Little research has been done on how to make analysis results transparent so that it is possible for persons from the outside to trace and verify them. Furthermore, few articles have studied reasoning in a spatial context. Spatial relations are the basic pillars of conceptualizing our world and they are part of the core vocabulary in our reasoning processes (Egenhofer and Mark 1995).

The aim of this paper was to develop concepts for making results of spatial analysis transparent by using visualizations. Developing knowledge representations of this kind that communicate the reasoning behind analysis results requires the identification of the knowledge used by the expert in the process of the analysis. To reach this aim, a review of what this knowledge is, and what part it plays in reasoning, was required. This review can be found in the next chapter, Theoretical Background. First, reasoning and knowledge are introduced from a cognitive perspective, and then theories of visual analytics and knowledge visualization, in both of which cognitive research plays an important role, are presented. The concept of expertise is also discussed. A case study was performed in which the principal knowledge used by an expert performing a specific spatial analysis task was identified and documented. The case study is introduced in Chapter 3. Then, the theories from Chapter 2 are applied to the case study and concepts of how to make the reasoning accessible for persons external to the process of analysis are proposed in Chapter 4. Finally, the conclusions can be found in Chapter 5.

2 Theoretical Background

2.1 Reasoning and Knowledge

Reasoning is the process by which, through a set of mental processes, we derive inferences or conclusions from a set of premises (Samarapungavan 2012). Reasoning is central to human thought and we use it all the time in our daily life. It helps us to generate new knowledge and to reorganize existing knowledge. It is essential for critical and creative thinking, argumentation, problem solving, and decision making.

Johnson-Laird (2006) states that deduction and induction underlie all types of reasoning and that the principal difference between reasoning in different fields is in contents, not in processes. *Deductive reasoning* is based only on the information given in the premises and on logic. It is the process of establishing that a conclusion is a valid inference from premises. A correct deduction yields a conclusion that must be true, given that the premises are true (Samarapungavan 2012).

Any other type of reasoning is based on induction. Contrary to deductive reasoning, *inductive reasoning* goes beyond the given information and rules out more possibilities than the premises do (Johnson-Laird 2006). This is possible because inductive reasoning depends on knowledge not given in the premises. By going beyond the given information, by using existing knowledge, inductive reasoning results in new knowledge. However, induction does not guarantee logically valid inferences and conclusions, and therefore the new knowledge may be fallible.

In this respect knowledge is defined through the terms information and data (as in Keller and Tergan 2005). Data are symbols or isolated and non-interpreted facts; they are raw. Information is data in a context; it is data that have been given meaning through interpretation. Knowledge is information which has been cognitively processed and integrated into an existing human knowledge structure. Thus, knowledge only exists inside our brains.

2.2 Induction and Causal Models: Human Reasoning in Practice

Inductive reasoning is the cornerstone of human reasoning because we are only moderately good at deductive logic and we make only moderate use of it (Arthur 1994). Computers, on the other hand, are good at deductive logic because of their superior memory.[1] By forming a *complete model* of the possibilities for each of the premises, and by making a conjunction of the complete models, a computer program can represent, in a complete and fully explicit way, the set of possibilities that satisfies the premises (Johnson-Laird 2006).

[1] Computers are also capable of inductive logic. For example, expert systems that solve diagnostic problems are based on inductive reasoning (Angeli 2010).

Humans can cope with simple deductive problems but in complicated situations our ability for deductive reasoning brakes down (Arthur 1994). There are two reasons for this. One is that beyond a certain level of complexity human logical capacity ceases to cope, mainly because of our limited working memory. The other reason is that in complicated situations an actor cannot rely upon other agents to behave in a perfectly rational way; they are forced to guess their behavior. Deductive reasoning, which derives a conclusion by perfect logical processes from well-defined premises, cannot apply under such conditions.

Thus, when problems are complicated we rely on inductive reasoning. We use the meaning of premises and our knowledge to construct *mental models* that contain less information and impose fewer demands on working memory than complete models do (Johnson-Laird 2006). However, mental models represent only what is true, i.e., what is possible, as opposed to complete models which represent both what is true and false in each possibility. Therefore mental models can make us draw false conclusions. Figure 1 provides a schematic overview of deductive and inductive reasoning and the difference between them.

Pattern detection is an essential part of inductive reasoning and we use it in order to simplify a problem (Arthur 1994). One source of patterns in our world is causality, i.e., the relationship between two events, where the second event, the *effect*, is a consequence of the first event, the *cause*. Sloman (2005) argues that according to human perception, the world is full of causal systems composed of autonomous mechanisms that generate events as the effects of other events and that this is how we understand the world we live in.

That these relations of cause and effect are an essential part of inductive reasoning is something that was already argued by David Hume (1748). Sloman (2005) explains that the mental models we use when we reason are often causal models and their task is to explain what generated the perceived sensory input. More generally, universal conclusions drawn from particular facts are commonly mediated by the construction of a causal model to explain the facts. In these cases, conclusions drawn by inductions are just descriptions of a causal model or some causal relation embedded in it.

Also counterexamples are crucial for human reasoning (Johnson-Laird 2006). A *counterexample* establishes that a conclusion is false in at least one possibility consistent with the premises, i.e., that the conclusion is not a valid inference from the premises. By counterexamples we can test whether our inductive conclusions are valid.

2.3 Reasoning and Expertise

As already concluded, inductive reasoning relies on knowledge and mental models. It is a continuous process of updating the confidence or strength of a belief (Rips 1990). We learn which mental models work and discard those that do not. A model is clung to not because it is correct, but because it has worked in the past. It must accumulate a record of failure before it is worth discarding (Arthur 1994).

Through experience our knowledge base grows and we develop our mental models so that they work better and better. With enough training and experience in a certain domain we become experts. Experts have the best mental models and therefore they can draw more accurate inferences than the rest of us. Furthermore, as a result of their experience they have a large number of counterexamples with which to verify their inferences.

According to Sloman (2005), the distinguishing quality of the mental models of experts is that they pick out the invariants. Invariants are the properties that explain why the system is in its current state and that predict the state of the system in the future. They do not change across instances or across time. Expertise derives from knowing what is invariant. Actually, all human observers intuitively try to identify invariants from what they observe. And this leads us back to causality, because we should not look for invariants in the constantly changing physical world, but in the causal processes that govern change. It is these causal principles that are the carriers of information, and it is these principles, not the mechanisms they govern, that persist across time and space.

2.4 The Reasoning Process in Spatial Analysis

The goal of analysis is to reach conclusions through reasoning. (Thomas and Cook 2005). The reasoning process of an analyst performing an analysis task can be understood through the sense-making loop. The loop has four steps (Pirolli and Card 2005): (1) information gathering, (2) re-representation of the information in a form that aids analysis, (3) the development of insight through the manipulation of this representation, and (4) the creation of some kind of product or action that is based on the insight. Analysis is always iterative, so the steps of the sense-making loop can be repeated. From a reasoning perspective step 3, the development of insight, is the most interesting. In this step the analyst identifies or creates tangible pieces of information that contribute to reaching insights and forming defensible judgments. These pieces of information are called *reasoning artifacts*. They can, for example, be visualizations created during the analysis process or patterns identified on a map, and they are crucial in the reasoning process. Using these reasoning artifacts the analyst builds on his knowledge and forms *chains of reasoning* that articulate and defend the judgments made.

Spatial analysis follows the steps of the sense-making loop described above. In step 2 statistical or mathematical or even purely visual methods are used for the analysis of the given data. For example, in spatio-statistical analysis the empirical data set is compared with a mathematical probability model by calculating specified statistical measures from the data set (step 2 above) and comparing them to the values that represent the model (O´Sullivan & Unwin 2003). If the observed pattern of data seems to be a likely realization of the hypothesized process, the analyst can make a conclusion about the behavior of the phenomenon that was described by the empirical data set (step 3 above). In computational and exploratory methods, where there is no hypothesis and no existing model to compare with, the same process can be seen; but the outcomes of the computational method (for example clustering) are visualized and the interpretation and conclusions are based on the insight of the analyst (Nikander 2012). In this kind of visual analysis the reasoning artifacts mainly consist of information identified in visual representations, for example a map.

According to Thomas and Cook (2005), the knowledge representations that are needed to capture, store, and reuse the knowledge that is created must retain the reasoning artifacts that are produced throughout the process of analysis. They should also retain the chains of reasoning and links to supporting information associated with each analytical product.

In spatial analysis processes a lot of reasoning takes place and if the chains of reasoning are not documented and stored the argumentation is lost and the result can be questioned.

2.5 Knowledge Visualization

When knowledge is defined in the way it is in this paper it can only exist in our brains and thus its transfer is not straightforward. There is no such thing as direct knowledge transfer between individuals (Burkhard 2005). In the same way as information is converted into knowledge once processed in our minds, knowledge becomes information once it is articulated and explicated to a physical carrier. The research field of Knowledge Visualization addresses this problem.

Knowledge Visualization, the use of visual representations to improve the transfer and creation of knowledge, embraces all the graphic means that can be used to develop or convey insights, experiences, methods, or skills (Burkhard 2005). While information visualization typically solves problems of complex information structures, focusing on human-computer interaction, knowledge visualization is intrinsically connected to the problem of knowledge transfer in social structures, with an emphasis on the relationship between knowledge and humans (Novak and Wurst 2005).

Burkhard (2005) introduced four perspectives that need to be considered when creating visual representations that aim at transferring knowledge.

- Function type
- Knowledge type
- Recipient type

- Visualization type

Of these, function type, i.e., the aim of the representation, and recipient type, i.e., who is being addressed, are usually known beforehand. The knowledge type perspective addresses the content of the representation. There are different ways to categorize knowledge into types but in the literature there is no consensus about these categories yet. The last perspective is about finding the most suitable way to represent the knowledge.

3 The Setting of the Case Study

The aim of the case study was to identify and document the principal knowledge used by an expert performing a specific spatial analysis task. For this purpose a spatial analysis process was chosen and the reasoning in one phase of it was identified, documented, and made accessible for persons external to the process of analysis. This phase requires reasoning about complex spatial phenomena and is therefore representative for spatial analysis. The analysis process, which is based on the concepts of exploratory analysis and visual analytics, along with a software prototype that realizes it, was developed by Nikander et al. (2012).

3.1 Background

The analysis process concerns what is called a suitability problem, more exactly suitability for off-road mobility. The goal is to create a map that shows how difficult it is for a specified vehicle to advance in the terrain. The area is classified into subareas that cannot be crossed (NO GO), where the maximum practical speed is low (GO SLOW), and where it is possible to drive fast (GO).

This analysis process was developed for use in crisis management, in which numerous different organizations are involved, and where these organizations usually do not trust analyses performed by other organizations (Virrantaus et al. 2009). Usually they ask for raw data instead of ready-made analysis results.

One of the main reasons for the lack of trust is that the analysis processes are typically not revealed to other parties, making it impossible to study the reasoning behind the analysis results. In crisis management it is not possible either to know beforehand exactly what kinds of data will be available or what kind of problems need to be solved. Therefore, the analysis process needed to be *neutral,* i.e. leave the reasoning to the analyst, and *general* so that it can be used in different situations using whatever data are available.

As a consequence, the software prototype was designed to take various source data sets, in the form of gridded map layers in which each grid cell was taken as an object with attribute values, as its input and use the concept of *similarity* to create the mobility map. Similarity can be calculated as a distance in multi-dimensional space. The suitability problem is solved by combining similar locations into classes, because it is assumed that similar areas are also equally suitable for any purpose. The application uses *clustering* to organize the subareas into classes on the basis of their similarity. The clustering methods used are K-means (MacQueen 1967) and DBSCAN (Ester et al. 1996).

The clustering methods are neutral in the sense that they do not themselves solve the suitability problem. The user needs to interpret and classify the output according to the suitability for off-road mobility. This is done using linked views of a topographic map and a parallel coordinates plot (PCP). The map gives additional information about the topography and the PCP is used to give an easy visualization of the clusters data contents.

3.2 Description of the Analysis

The output interpretation window (Figure 2), which is used for the classification of the clusters, is divided into four frames. In the upper part are a map visualization frame and an information visualization frame showing the PCP. The different clusters are visualized using different colors and the user can select individual clusters or pixels for highlighting or more detailed analysis. The highlighting is reflected by both frames. In the case of Figure 2 the three first axes of the PCP stand for the three input data layers, slope, soil type, and amount of vegetation (for these the y-axis represent the mobility value of each input data layer). The fourth axis is the cluster number. In the lower part of the output interpretation window the output interpretation frame, containing a functionality for assigning suitability labels to the clusters, can be found on the left, and on the right there are details about the cluster, showing the centroid of each cluster and all the data vectors belonging to each cluster.

In the output interpretation window the user can see the details of each cluster. In the map frame there is the spatial distribution of each cluster and the information visualization frame shows how the clusters are distributed in the attribute data space and the data vectors belonging to each cluster. Using this information, i.e., the spatial distribution and the mobility values included in each cluster, the user labels each cluster according to its mobility. When this is done the map can be colored according to the mobility.

4 Results

In the case study the knowledge used by the analyst in the analysis process was identified along with the demands that the nature of this knowledge puts on the representation of it. Then, concepts for making analysis results transparent were developed. The four perspectives on visual knowledge representations introduced by Burkhard (2005), given above in 2.5 Knowledge Visualization, worked as a starting point when the concepts were developed.

4.1 Spatiality and Causality in the Reasoning Process

In spatial analysis we reason about complex spatial relations and complex problems. This reasoning is inductive, as we have to rely on inductive reasoning in complicated problems, and thus it depends on knowledge. The reasoning artifacts that the analyst identifies and the chains of reasoning he forms are a part of that knowledge and they need to be captured and stored so that the decisive pieces of information in them can be identified. As spatial relations are important for the reasoning in spatial analysis it must be made certain that also the spatial relations are captured.

The reasoning in the analysis phase in the case study was about whether a cluster should be labeled GO, GO SLOW, or NO GO. This reasoning is aided by the spatial distribution of each cluster shown on the map and by how the clusters are distributed in the data space which is shown in the PCP. These two visualizations, the map and the PCP, are the reasoning artifacts used by the analyst, and the decisive pieces of information that the analyst identifies in the reasoning process must therefore be located in these visualizations.

This information often takes the form of complex spatial and thematical relations that cannot be articulated in words. However, it can be expressed by making sketches on top of the map and the PCP. Sketches are good for this purpose as they are versatile and easy and fast to create and process (Burkhard 2005). By sketching on top of a reasoning artifact the decisive pattern or relations can be identified exactly. This way the important *spatial relations* are captured.

In the case study the chains of reasoning of the analyst defend labeling decisions, i.e., conclusions. According to Sloman (2005) conclusions drawn by induction are commonly mediated by the construction of a causal model to explain the observed facts. In our study the analyst reasons in terms of what causes what, i.e., the characteristics of a cluster lead to the labeling decision. The chains of reasoning are the chains of causes that eventually led to the final labeling decision, they are the causal model. Therefore, the structure for storing the chains of reasoning needs to capture the *causal relations* inherent in them. Diagrams can do this as they are structured, systematic, and good at explaining causal relationships and help to reduce complexity (Burkhard 2005). Therefore a causal graph that displays the relationships between causes and effects was developed for this purpose.

4.2 Making the Reasoning Accessible

Storing the reasoning artifacts, with accompanying sketches, and the chains of reasoning, in the form of causal graphs, are the basic building blocks for making the reasoning accessible to people external to the analysis process. For the causal graphs to be fully understandable they need to be linked with the corresponding reasoning artifacts, i.e., the map and the PCP that were used for making the decision. If sketches were made they need to be linked to the part of the causal graph that explains what the sketch is about. To further facilitate the understanding of the reasoning a comment by the analyst explaining the analysis should be added. These kinds of textual representations are a good complement to the diagrammatic representation in the causal graph and the visual representation in the form of sketches on top of the map and PCP.

These three components work together to make the reasoning transparent. Figure 3 shows an example of what it could look like for a specific cluster. The map and PCP associated with this cluster are in the upper part of the figure. The causal graph related to the cluster can be found in the middle. Each box contains one cause expressed by a few words. The arrow from each box depicts how the reasoning process progressed from one cause to the next until a decision was reached. As can be seen, there are actually three parallel chains of reasoning that led to the decision. In this case the analyst started by noting the soil, slope, and vegetation values included in the cluster. The soil and slope were established as being well suited for off-road mobility. On the other hand, the vegetation was initially considered to be unsuitable but closer inspection made the analyst realize that this type of vegetation can easily be cleared. It was suitable for off-road mobility after all. Therefore the final decision was to label it GO SLOW.

The causal graph is linked to the map and the PCP. In the example the user has put the mouse cursor on top of the box marked ‘unsuitable vegetation’, making the associated sketches become visible on the PCP. The box is highlighted with a red border and the marks relating to this cause can be seen in red on the PCP. In the bottom are the comments made by the analyst regarding this cluster.

Figure 4 exemplifies how the spatial relations in the data can be decisive for the classification decision. Initially the cluster seems to be NO GO as the slope and soil values are unsuitable. However, after a closer inspection using a topographic map the analyst realizes that the cluster is spatially very small and coincides with major roads and is therefore GO. He concludes that it must consist of rock cuttings and therefore it had bad mobility values. The regions marked with purple in the map indicate the information that made the analyst realize that this is the case.

The colors and symbols in the causal graph are additional information carriers. The color tells us what input data the reasoning is based upon; in the case of Figure 3 each reasoning chain concerns different input data. The symbols in the upper right-hand corner of the boxes inform us where the cause was found. In our case the alternatives are the map, the PCP, or neither of these.

5 Conclusions and Future Research

An important result of this paper is the identification of the knowledge used by the analyst in the case study. The knowledge consists of the reasoning artifacts and the tangible pieces of information identified in them, along with the mental models of the analyst´s mind. These mental models take the form of chains of reasoning in the analysis process. This paper shows that the reasoning theories of visual analytics are applicable to spatial analysis. By combining them with general theories of human cognition from research on reasoning and causality, this paper improves their credibility and develops them further. The chains of reasoning in the case study were concluded to be causal in their nature and it is likely that this is also true for analysis in general as conclusions drawn by induction are commonly mediated by the construction of a causal model.

This study presented two concepts for making analysis results transparent. The first, sketches on top of reasoning artifacts, utilizes the flexibility of sketches. The method allows the analyst to draw sketches on top of the reasoning artifacts used in the analysis process. It enables the analyst to point out the tangible pieces of information used in the reasoning on which the decisions were based. The concept of making sketches on top of reasoning artifacts is promising for application in spatial analysis as they enable an analyst to make tacit spatial knowledge explicit in ways that would not be possible by solely using words.

It was found that causality was central to the reasoning process in the case study. Therefore the other visualization concept, the causal graph, was designed to capture this causality by allowing the chains of reasoning of the analyst to be saved into a diagrammatic structure. The causal graph allows the reasoning of the analyst to be studied, as well as traced back to its origin, i.e., the tangible pieces of information that it is based upon. This is achieved by linking the graph to the sketches made on top of the maps and the PCPs created during the analysis.

Topics for future research include both how the documented reasoning can be developed into more formal presentations by using spatial predicates and the development of the visualization concepts of this research. Instead of the freeform verbal argumentation in the causal graph a more structured presentation of knowledge could be beneficial. The visualization concepts developed in this research were just a demonstration of how the reasoning can be made accessible and they can still be improved a lot.

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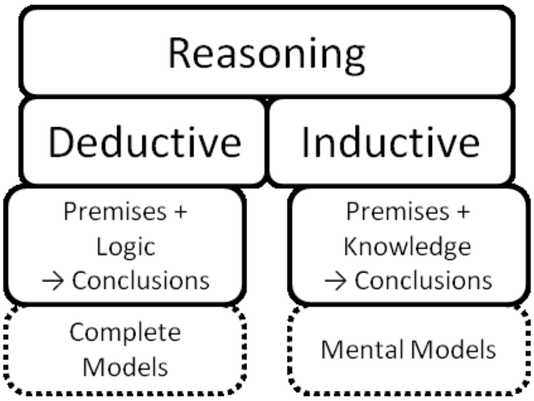

Figure 1 A schematic overview of deductive and inductive reasoning.

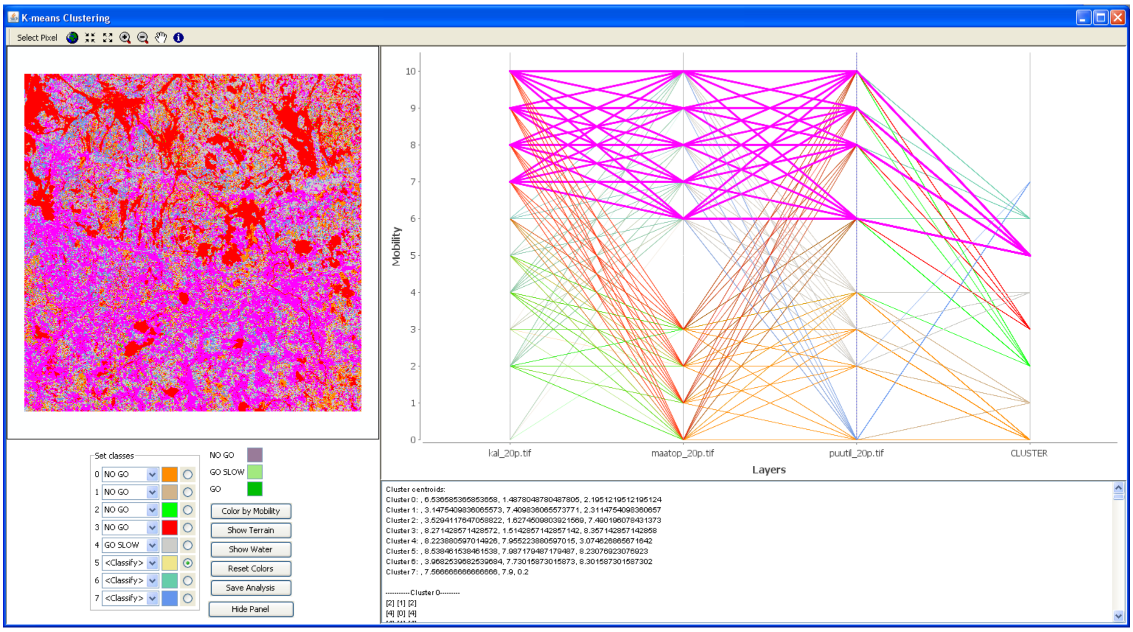

Figure 2 The output interpretation window in the prototype application used for the case study. Here cluster 5 is selected and marked with purple in the PCP and on the map. (Nikander 2012)

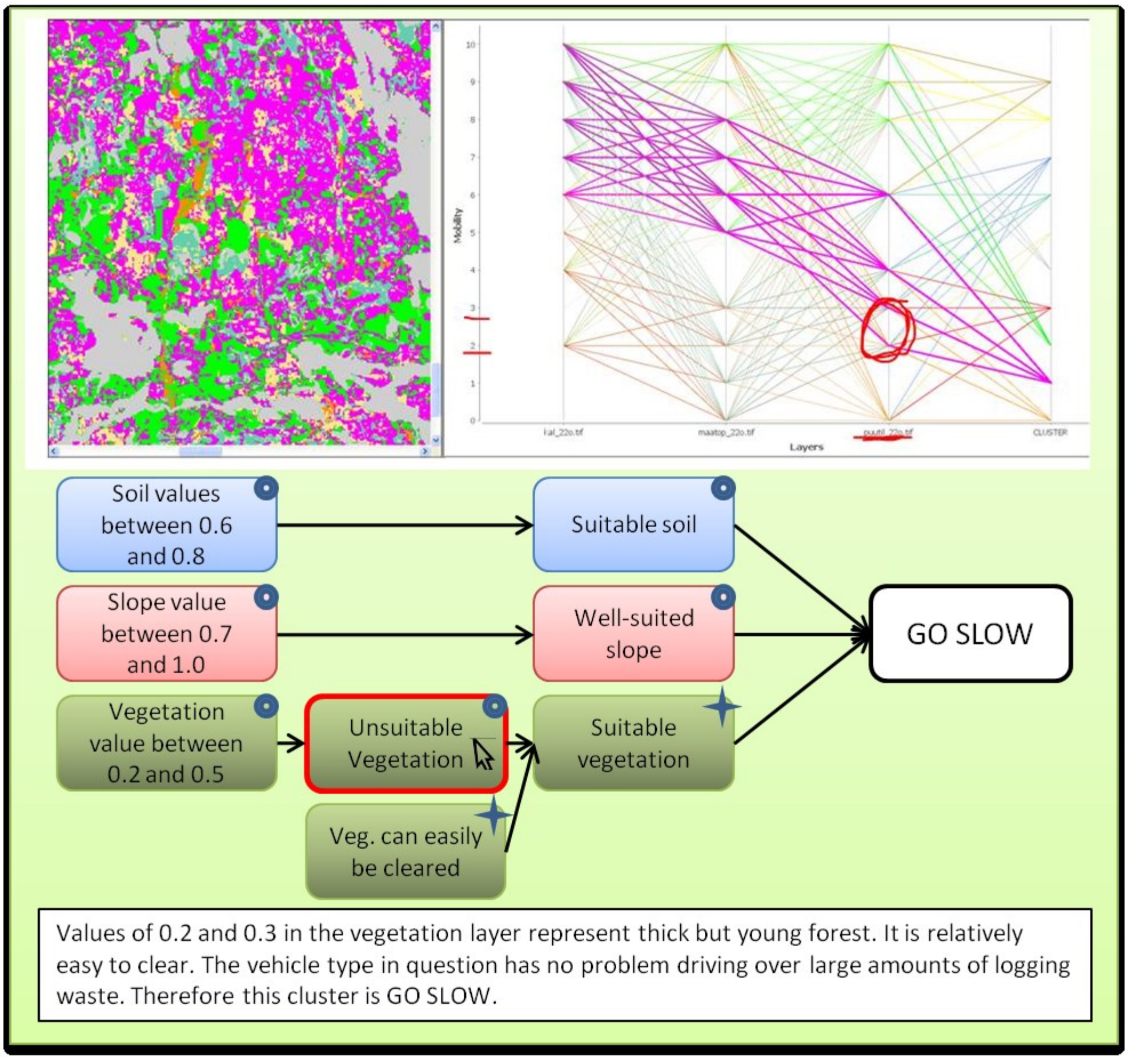

Figure 3 The reasoning artifacts, the causal graph and the comment related to a specific cluster linked together. Here the user has selected the box saying 'Unsuitable Vegetation' which makes the related sketch appear on the PCP.

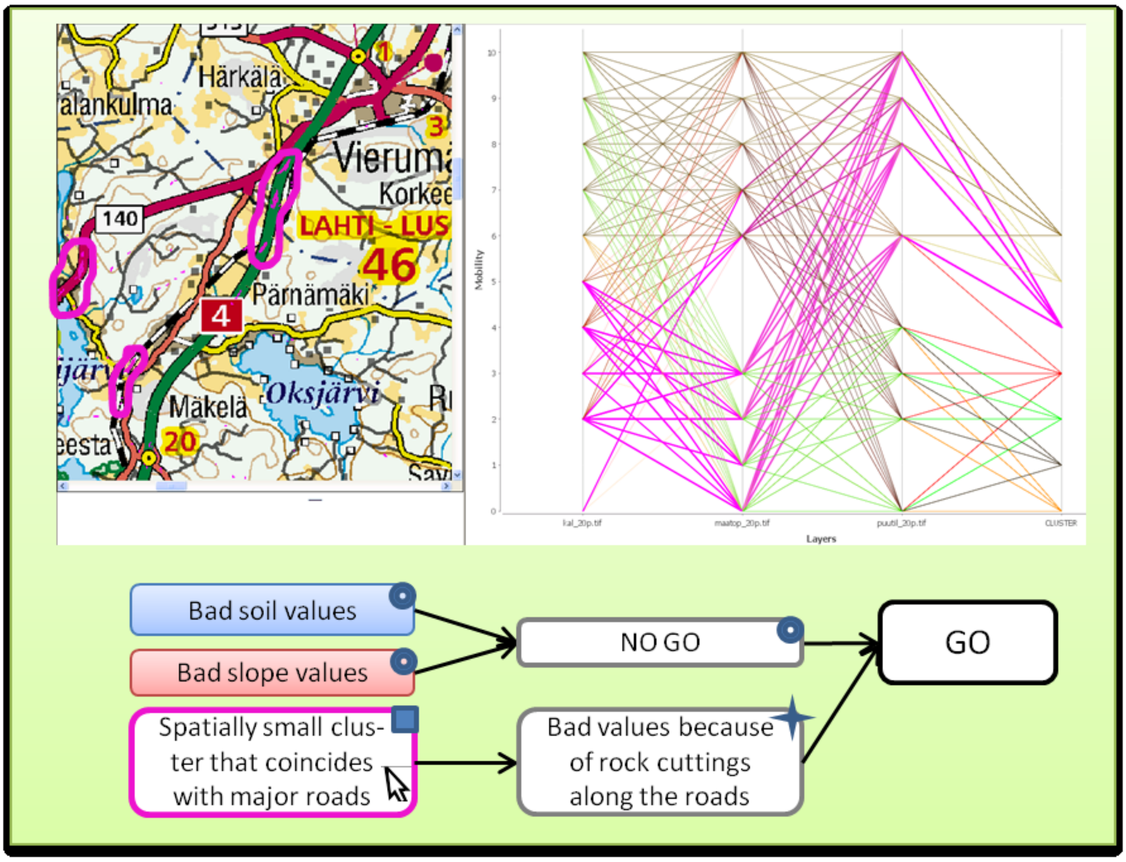

Figure 4 In this example, the spatial aspects of the data are decisive for the final decision.

Figure 1 A schematic overview of deductive and inductive reasoning.

Figure 2 The output interpretation window in the prototype application used for the case study. Here cluster 5 is selected and marked with purple in the PCP and on the map. (Nikander 2012)

Figure 3 The reasoning artifacts, the causal graph and the comment related to a specific cluster linked together. Here the user has selected the box saying ‘Unsuitable Vegetation’ which makes the related sketch appear on the PCP.

Figure 4 In this example, the spatial aspects of the data are decisive for the final decision.